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INTELLIGENCE SYSTEM OF ARTIFICIAL VISION FOR UNMANNED AERIAL VEHICLE

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ІНТЕЛЕКТУАЛЬНА СИСТЕМА ТЕХНІЧНОГО ЗОРУ ДЛЯ БЕЗПІЛОТНИХ ЛІТАЛЬНИХ АПАРАТІВ

Abstract. The article considers the method of factor cluster analysis which allows automatically retrain the on-board recognition system of an unmanned aerial system. The task of informational synthesis of an on-board system for identifying frames is solved within the information-extreme intellectual technology of data analysis, based on maximizing the informational ability of the system during machine learning. Based on the functional approach to modeling cognitive processes inherent to humans during forming and making classification decisions, it was proposed a categorical model in the form of a direct graph. According to this model, the algorithmic support of the information-extreme factor cluster analysis is developed. It allows automatically retrain the system when expanding the alphabet of recognition classes. According to this algorithm, the on-board recognition system preliminarily carries out the information-extremal machine learning of recognition classes of relatively low power. When new classes appear, their unclassified structured recognition attribute vectors form additional learning matrixes. After reaching a representational volume, additional learning matrix joins the input learning matrix and the on-board recognition system is retrained. Forming additional learning matrixes of new recognition classes is carried out by the agglomerative algorithm of cluster analysis of unclassified vectors by k-means clustering. As a criterion of optimizing machine-learning parameters, we used the modified Kullback criterion which is a functional of the exact characteristics of classification solutions. To increase the functional efficiency of factor cluster analysis, it is proposed to increase the depth of machine learning by optimizing the parameters of image processing frames.

Keywords: Information-extreme machine learning; Identification; Digital image frame of the region.

Анотація. Розглядається метод факторного кластер-аналізу, який дозволяє автоматично перенавчати бортову систему розпізнавання безпілотного авіаційного комплексу при ідентифікації кадрів, сформованого по оптичному каналу цифрового зображення регіону. Задача інформаційного синтезу бортової системи для ідентифікації кадрів розв’язується в рамках інформаційно-екстремальної інтелектуальної технології аналізу даних, яка базується на максимізації інформаційної спроможності системи в процесі машинного навчання. У рамках функціонального підходу до моделювання когнітивних процесів, притаманних людині при формуванні та прийнятті класифікаційних рішень, запропоновано категорійну модель у вигляді орієнтованого графу. Згідно з категорійною моделлю розроблено алгоритмічне забезпечення інформаційно-екстремального факторного кластер-аналізу, що дозволяє автоматично перенавчати бортову систему розпізнавання при розширенні алфавіту класів розпізнавання. За цим алгоритмом бортової системи розпізнавання попередньо здійснює інформаційно-екстремальне машинне навчання за алфавітом класів розпізнавання відносно малої потужності. При появі нових класів розпізнавання їх некласифіковані структуровані вектори ознак розпізнавання утворюють додаткові навчальні матриці. Додаткова навчальна матриця, яка досягає репрезентативного обсягу, приєднується до вхідної навчальної матриці та здійснюється перенавчання бортової системи розпізнавання. Формування додаткових навчальних матриць нових класів розпізнавання здійснюється за агломеративним алгоритмом кластер-аналізу некласифікованих векторів за методом k-середніх. Як критерій оптимізації параметрів машинного навчання було використано модифікований критерій Кульбака, який є функціоналом від точнісних характеристик класифікаційних рішень. Для підвищення функціональної ефективності факторного кластер-аналізу пропонується збільшити глибину машинного навчання шляхом оптимізації параметрів оброблення зображень кадрів.

Ключові слова: інформаційно-екстремальне машинне навчання; ідентифікація; кадр цифрового зображення регіону.

Introduction

Unmanned aerial systems are widely used to search ground vehicles. Therefore, the urgent task is to provide the onboard recognition system (ORS) with independence based on machine learning and pattern recognition [1]. The main approach to detecting ground ob-jects is the use of descriptive methods. Their main disadvantage is the uncertainty during recognizing objects of the same sizes. The use of neural-like structures for the analysis of digital images of ground objects also does not solve the problem of increasing the functional efficiency of the ORS due to their sensitivity to the multi-dimensional dictionary of recognition signs. As one of the promising directions of increasing the ORS functional effectiveness is applying ideas and methods of the so-called information-extreme intellectual technology (IEI technology) of data analysis [8]. Its methods simulate the cognitive processes inherent to humans when forming and making classification decisions in the most appropriate manner. [2, 3].

The article is devoted to the information-extreme method of ORS machine learning to identify the digital image frames of the observation region, which operates in the mode of factor cluster analysis (FCA) [7].

Research objective

Let us consider a formalized statement of the problem of informational synthesis of an onboard frame identification system that operates in the FCA mode. There is formed an alphabet $\{X_m^o | m = \underline{1, M}\}$ of recognition classes characterizing the image frames of the area. For each recognition class a three-dimensional learning matrix $||y_{m,i}^{(j)}||$ of pixel brightness of the frame receptive field is formed, where the row $\{y_{m,i}^{(j)} | i = \underline{1, N}\}$, N − number of recognition features, is a structured feature vector of the corresponding recognition class (hereinafter, simply implementation), and the matrix column − random training set $\{y_{m,i}^{(j)} | j = \underline{1, n}\}$ with volume n.

It is known that the concept of IEI tech-nology involves transforming the input learning matrix Y into a working binary matrix X, which changes during machine learning. Therefore, for the Hamming binary space, a vector of functi-oning parameters is set. They affect the functi-onal efficiency of ORS machine learning in recognizing recognition class implementations X_m^o:

$$g_m =< x_m,\ d_m,\ \delta >, \quad (1)$$

where xm – implementation ensemble-averaged vector, its vertex defines the center of the hyperspherical container of the recognition class X_m^o; d_m – radius of hperspherical container recognition class X_m^o, which is restored in the radial basis of the recognition feature space; δ – a parameter the of which is equal to half the symmetric field of the control tolerances divided by recognition signs which are the brightness values in pixels. The following restriction are imposed on the parameters of system functioning, further called the parameters of machine learning:

- the range of pixel brightness values is in the range [0; 255] of tone gradation;
- recognition radius container range X_m^o is given by inequality $d_m < d(x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ – center-to-center distance between the implementation x_m and the nearest implementation x_c of the next class X_c^o;
- parameter range space δ is given by inequality $\delta < \delta_H/2$, де δ_H – standard tolerance limit for recognition features.

It is necessary to optimize the vector parameters (1) at the stage of ORS machine learning, which provide the maximum value of the information optimization criterion in the working (accessible) area of determining its function:

$$\underline{E}^* = \frac{1}{M}\sum_{m=1}^{M} \max_{G_E \cap \{k\}} E_m^{(k)}, \quad (2)$$

where $E_m^{(k)}-$ the value of information crite-rion for optimizing learning parameters of the system to recognize class implementa-tions X_m^o calculated on the k learning step; G_E- workspace for calculating an informa-tion criterion; $\{k\}-$ number of learning steps. In the exam mode basing on unclassified im-plementations of recognition classes which characterize new frames of the image it is necessary to form additional learning mat-rixes. After reaching the representational vo-lume they join the input learning matrix and, in such a way, the ORS is retrained.

Computational model

In terms of functional approach, the cate-gorical model of information-extremal machine learning is built in the form of a directed graph [4]. Thus, the input mathematical formulation of the category model is presented in the form of a following structure

$$\Delta B =< G,\, T,\, Z,\, \Sigma,\, Y,\, X;\, F,\, \Phi,\, \xi >,$$

where G − factors influencing the ORS; T − time points for receiving information; $\Sigma-$ recog-nition features dictionary; Z – space of system states, (alphabet of recognition classes); − input multidimensional learning matrix; $X-$ working binary learning matrix; $F\colon G \times T \times Z \to \Sigma-$ operator for forming recognition features dictionary; Φ–operator for forming the input learning matrix Y; $\theta_1\colon Y \to X-$ operator for transforming Y matrix into a working binary matrix X; $\xi-$ operator for expanding the matrix Y.

Figure 1 shows categorical model of informational and extreme machine learning for ORS in the FCA mode.

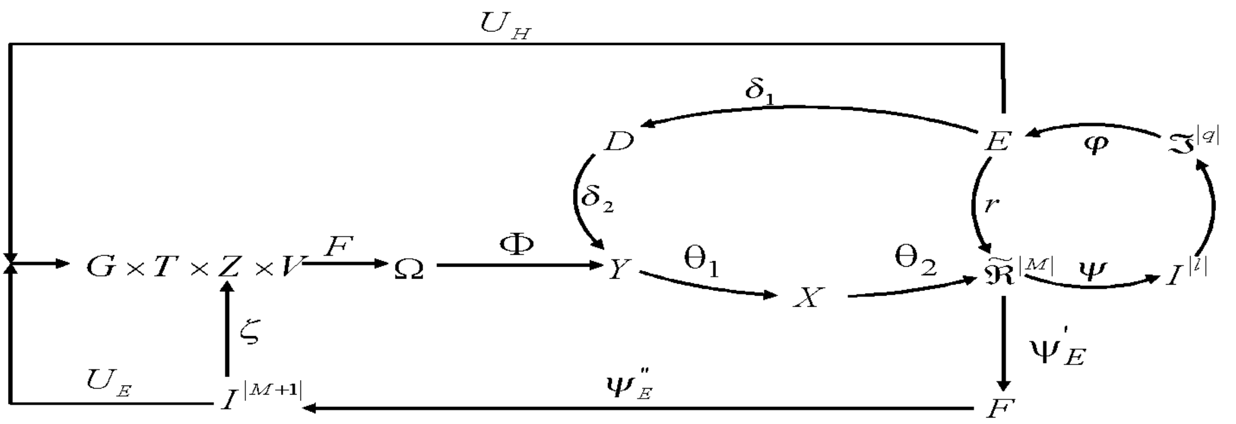

Fig. 1. FCA categorical model

In the circuit that simulates the operation of ORS in machine learning mode, the operator θ_2 reflects the implementations of the working matrix into a fuzzy partition $\tilde{R}^{|M|}$ of recognition classes. Classification operator $\Psi\colon \tilde{R}^{|M|} \to I^{|l|}$ checks the basic statistical hypothesis about the belonging the implementation $x_{m,h}^{(j)}$ to class $X_{m,h}^o$ and generates hypotheses $I^{|l|}$, where $l-$ number of statistical hypotheses. Basing on the results of statistical hypotheses operator $\gamma\colon I^{|l|} \to I^{|q|}$ forms a number of accuracy characteristics $I^{|q|}$, where $q = l^2$. Operator $\phi\colon I^{|q|} \to E$ calculates the set of values of the information criterion for optimizing machine-learning parameters. At each step of machine learning the operator in the radial basis of the feature space restores recognition containers that form a partition $\tilde{R}^{|M|}$. The circuit for op-timizing acceptance tolerance for recognition features is closed due to term set D – accep-tance tolerance framework.

In the circuit that simulates the opera-tion of ORS in the exam mode, or directly in the operating mode, the classification ope-rator of the examination recognition vector forms a composition, $\Psi_E = \Psi'_E \circ \Psi''_E$, where the operator Ψ'_E calculates member-

ship functions and forms a term set F, while the operator Ψ''_E calculates decision rules.

According to the exam results, a set of hypotheses $I^{|M+1|}$ is formed. Among them the hypothesis γ_{M+1}means that the examination implementation does not belong to the alphabet of recognition classes $\{X_m^o | m = \overline{1, M}\}$. An operator ξ basing on unclassified implementations generates an additional learning matrix, and, after reaching the minimum representative volume, adds to the input learning matrix Y and starts the process of ORS retraining. Operators U_H and U_E regulate machine learning and exam processes accordingly.

The categorical model (Fig. 1), built as part of a functional approach to modeling cognitive processes for the formation of classification decisions, is a generalized scheme of the information-extreme FCA algorithm.

Implementation notes of information-extreme factor cluster analysis algorithm

The ORS machine learning algorithm with optimization of acceptance tolerance for recognition features is represented in the form of a two-cycle procedure for finding the global maximum of information criterion [2]:

$$\delta_K^* = \underset{G_\delta}{argmax}\{\underset{G_E \cap \{k\}}{max} \underline{E}^{(k)}\}, \quad (3)$$

where δ_K^* – optimal parameter of the acceptance tolerance field; δ_K^*– allowed value area of parameter δ of acceptance tolerance field; $\{k\}$– time ordered set of machine learning steps.

Based on the optimal geometric parameters of the containers of recognition classes obtained during machine learning, production decision rules are built in the form of:

$$(\forall X_m^o \in R^{|M|})(\forall x^{(j)} \in R^{|M|}) \; [if \; (\mu_m > 0)(\mu_m = max\{\mu_m) \quad then \; x^{(j)} \in X_m^o \;\; else \; x^{(j)} \notin X_m^o], \quad (4)$$

where $x^{(j)}$ – vector that is recognized; μ_m– membership function of vector $x^{(j)}$ to a recognition classX_m^o.

In expression (4), the membership function for a hyper spherical container of recognition class X_m^o is determined by the formula [3]

$$\mu_m = 1 - \frac{d(x_m^* \oplus x^{(j)})}{d_m^*},$$

where x_m^*, d_m^*– optimal machine learning para-meters: averaged binary implementation and hyper spherical container radius, respectively.

When new recognition classes appear in the exam mode, their unclassified structured im-plementations form additional learning mat-rixes. An additional learning matrix, which reaches a representative volume, joins the input learning matrix and the ORS is retrained using an information-extreme algorithm. Forming additional learning matrixes of new recognition classes is carried out through an agglomerative algorithm of cluster analysis [5] of unclassified implementations. Accor-ding to this algorithm, the top point of the unclassified implementation is taken as the center of the recognition class X_{M+1}^o, around which the area of the corresponding radius is set. If another classified implementation falls into this area, the new center of the class X_{M+1}^o is determined according to the k-means clustering. An unclassified implementation does not fall into the class region, forms the center of a new class X_{M+2}^o. It continues until a certain number of clusters are built.

After that, the cluster radiuses increase and k-means clustering is implemented again. The clustering process continues until a representative additional learning matrix of a new recognition class is formed, which is connected to the input learning matrix and starts the process of ORS retraining.

Simulation results

According to the procedure (3), an algorithm for ORS information-extreme machine learning in the FCA mode was developed and implemented. As a criterion for optimizing the vector parameters (1), we used the modified Kullback criterion [2], [6]:

$$E_m^{(k)} = \frac{1}{n} log_2 \left\{ \frac{2n+10^{-r}-\left[K_1^{(k)}+K_2^{(k)}\right]}{\left[K_1^{(k)}+K_2^{(k)}\right]+10^{-r}} \right\} [n - (K_1^{(k)} + K_2^{(k)})], \quad (5)$$

where $K_{1,m}^{(k)}$ – a number of events when implementations belonging to a class X_m^o are not related to it accidentally; $K_{2,m}^{(k)}$– a number of events when the implementations of the neighboring recognition class X_c^o are accidentally related to recognition class X_m^o; 10^{-p}– a sufficiently small number to avoid divide by zero.

In our example, as a source image we used sand pit fragment obtained from air-photography. As recognition classes, we have chosen such image sections as: class X_1^o – dense forest; class X_2^o– sand plot; class X_3^o– road. The input learning matrix was formed by sequentially reading out the brightness values in pixels of the receptive field of each 50×50 pixels frame.

Figure 2 shows the dependency graph of the alphabetically averaged recognition class of information criterion (5) on the parameter δ of the acceptance tolerance field obtained during the ORS machine learning.

Fig. 2. Dependency graph of the criterion from the parameter of acceptance tolerance field

In Fig. 2 and further in the text, double shading denotes the working (allowed) domain of defining criterion function (5), where values $K_{1,m}^{(k)}$ and $K_{2,m}^{(k)}$ are less than 0.5. Analysis of Fig. 4 shows that the optimal parameter value of the acceptance tolerance field is equal to $\delta * = 32$ of tone gradation under the criterion maximum value $E_{max} = 4{,}20$.

Based on the optimal parameters of the recognition class containers, the decision rules (4) were built and the image frames of the region were identified. The analysis of the image digitized by the numbers of recognition classes showed that part of the frames indicated by 0 was not assigned to any of the recognition classes.

In order to verify the FCA algorithm, we input the implementations of three new frames: class X_4^o (soil), class X_5^o (sparse forest) and class X_6^o (earthroad) in the ORS, functioning in the exam mode.

After ORS retraining the learning matrix for six recognition classes, the maximum value of the alphabetically averaged recognition classes of the information criterion de-creased to 1.85, which is associated with an increase of intersection of recognition clas-ses in the feature space. To increase func-tional efficiency, the depth of machine lear-ning was increased by optimizing the accep-tance tolerance according to the scheme, involving sequential optimization of acceptance tolerance for all features. In such a case, acceptance tolerances obtained during parallel optimization were taken as starting ones.

Figure 3 shows a graph of changing the information criterion during the process of machine learning with sequential optimization of acceptance tolerances.

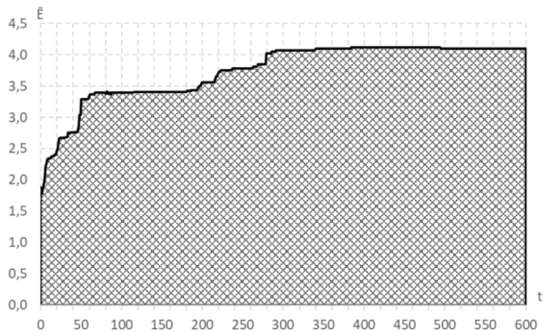

Fig. 3. Graph of changing the information criterion during sequential optimization of acceptance tolerances

Analysis of Fig. 3 shows that the information optimization criterion on the fourth iteration, the number of which is determined by the ratio of numbers of iterations $\bar{i}$ to the number of features N, has reached its maximum value $\underline{E}_{max} = 4{,}10$. In order to build decision rules (4), the optimal parameters of the recognition class containers were determined according to the dependence graphs of criterion (5) on the container radiuses were determined.

Figure 4 shows a digitized image of a region obtained with decision rules (4).

Fig. 4. Digitized image of a sand pit obtained according to the results of frame identification

Analysis of Fig. 4. shows that image frames with the number 0 contain exclusively images of objects of non-natural origin, for example, buildings or vehicles. The identification of image frames of the region allows determine the range of interest most probably containing the ground object of non-natural origin.

Summary

Within the functional approach, a categorical model is proposed, based on which an information-extremal machine learning algorithm for ORS in the FCA mode is developed. It allows automatically retrain the system when expanding the alphabet of recognition classes. The use of decision rules built within the geometric approach allows increasing the efficiency of making classification decisions due their low computational complexity. In addition, such decision rules are almost invariant to the multi-dimensionality of the space of recognition features.

The developed method for identifying image frames in a region allows to determine areas of interest which may contain ground objects of unnatural origin. To increase the functi-onal efficiency of the ORS, it is necessary to increase the depth of machine learning by optimizing additional parameters of machine learning.

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